UNIVERSITY OF VAASA

FACULTY OF BUSINESS STUDIES

DEPARTMENT OF FINANCE

Riku Lindstedt

PREDICTING FINNISH SME MANUFACTURING COMPANY BANKRUPTCIES WITH ALTMAN Z

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UNIVERSITY OF VAASA
Department of Accounting and Finance
Author: Riku Lindstedt
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Supervisor: Jussi Nikkinen
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ABSTRACT

The purpose of this thesis is to examine how Altman's Z-score models can predict bankruptcy. The Z-models contain weighted ratios derived from the financial statements. The sum and result of the model, called Z-score, reflects the bankruptcy potential of the company when the score is compared to discrimination zones.

The data of the thesis consists of financial statements of Finnish SME manufacturing companies. All the companies are unlisted. Data was collected from the Bureau van Dijk's Orbis database. The sample includes a total of 80 companies, of which forty were bankrupt and forty active. The sample of active companies is chosen on a stratified random basis. In the study, Z-scores are calculated for the sample, and examined how accurately the Z-models classified the companies between the non-bankrupt and bankrupt groups. Differences between the individual financial variables included in the models are also compared.

According to results, Altman's Z''-model's accuracy is decent when predicting Finnish SME manufacturing company bankruptcies. One year before bankruptcy, the model correctly classified 78% and two years before 71% of the companies. The model's ability to predict bankruptcy weakens significantly as the time horizon gets longer. Indeed, the classification results five years before the bankruptcy can be considered rather poor and the model does not have reliable long-term predictive power. An interesting result is the weak ability of Altman's Z' model to predict bankruptcy at any time. This is believed to be due to the fact that the model is beginning to be somewhat old in today's global economy.

KEYWORDS: Bankruptcy, Z-model, Financial ratios, Financial analysis

1. INTRODUCTION

1.1. Background and motivation

Increasing globalization is significantly increasing the competition between companies. Demand and supply may not always meet, and as a result, some businesses may lose customers. Only a small percentage of companies survive on the market when the weakest ones go bankrupt. In addition, many companies are increasingly exposed to supplier risk and similarities, as outsourcing volumes have grown significantly. International large-scale supply chains are increasing integration and thus the risk. Another important risk category in this area is the company's financial risk known as bankruptcy risk. (Jung, Lim & Oh 2011). Indeed, corporate bankruptcies have been under investigation for many decades, and there are no signs of declining interest.

Predicting bankruptcy has been an interesting research topic for almost a century and has been noticeable interest to business academics and financial economists over the last few decades (Altman 2002; Jones and Hensher 2008). Corporate bankruptcies can lead to significant economic costs for society and significant social changes through economic downturns and recessions. In the past two decades alone, the world has gone through several major corporate collapses, including the Asian Financial Meltdown in 1997, the Dot.Com bubble 2000 and 2002, and more recently the Global Financial Crisis of 2007-2008. (Jones and Hensher 2008).

There were 2534 bankruptcies in Finland in 2018 (Tilastokeskus). Bankruptcy refers to the procedure whereby the company's attachable assets are used to pay off creditors' claims (Konkurssilaki 120/2004). In the event of a bankruptcy, the company will incur significant losses for all its stakeholders. In order to counter the threat of bankruptcy of a company, it must first be noticed before-hand. Detection requires a functioning alert system that warns from symptoms before they break out. When it comes to the alarm system, the analysis of the different financial ratios and the bankruptcy predicting models developed on the basis of these ratios come into play. (Laitinen 2004: 19-23).

Beaver (1966) and Altman (1968) were among the first to develop statistical methods for predicting bankruptcy by using financial indicators. These studies have been the inspiration for many alternative models that have been developed to predict bankruptcy.

As more and more financial information becomes available all the time, interest in bankruptcy prediction is also increasing (Amendola, Bisogno, Restaino & Sensini 2011). Financial information published by companies is utilized in the calculation of financial ratios, so an increase in its availability may have a positive impact on the use of financial analysis. If more financial information is available, the results predicted by the indicators are also likely to be more reliable, or at least more diverse.

A model that can predict future bankruptcy as early as possible is very useful for different stakeholders. Specifically, a model that can produce reliable analysis, for large numbers of companies, and quickly and cheaply is certainly the desired tool for various stakeholders. The Z-models developed by Edward Altman (1968, 1983) are just such models. The Z-models combines financial ratios calculated from financial statements to form a weighted average to classify a company as a safe, gray or distress company. The models have been very popular due to their simplicity and flexibility. The popularity of the model is also partly based on the fact, that it can also be utilized by small and non-listed companies. The multiple discriminant analysis behind the Z-model is the most studied method in the field of bankruptcy prediction. (Pompe & Bilderbeek 2005).

1.2. Purpose of the study and hypotheses

The purpose of this thesis is to determine whether financial ratios, especially Altman's Z-models, can predict Finnish manufacturing company bankruptcies. In order to predict bankruptcies, financial ratios must differ between an active and functioning company and a bankrupt company. Thus, the first hypothesis of this study is as follows:

H1: Financial ratios differ between non-bankrupt and bankrupt companies.

Papers focusing on bankruptcy forecasting have often used large and listed companies, significantly fewer studies have focused on small businesses (Pompe & Bilderbeek 2005). However, the focus of this paper is particularly in Small and Medium Size enterprises (SMEs) since most of the operating and bankrupt companies are in this category.

Moreover, Small and Medium-sized Enterprises (SMEs) are considered as the backbone of the economy of many countries around the world. For example, in OECD countries the percentage of SMEs out of total number of companies is more than 97 percent. With a flexible and simple structure, SMEs are capable to respond quickly and effectively to changes in economic environment, sometimes growing into big and powerful companies or failing almost immediately after the company establishment. Thus, SMEs are very dynamic, involving a lot of changes and uncertainty compared to large companies. (Altman & Sabato 2007).

Dietsch and Petey (2004) use one-factor credit risk model to study default probabilities and asset correlations with large sample of German and French SMEs and conclude, that they are riskier but have a lower asset correlation with each other compared to large businesses. Thus, it can be assumed that the bankruptcy forecasting model developed for large companies gives different results when utilized the model with SMEs. Presumably, entire corporate portfolio consisting SMEs and large corporates will result in lower predicting power than the separate models for each.

Altman (1983) introduced a successful Z'-model developed for private manufacturing firms. Based on this research, the developed model is able to predict private manufacturing firms with better probability than the original Z-model developed in 1968.

In this thesis, the Z'-model will be utilized for testing it with Finnish SME manufacturing data. Hence, the second hypothesis is as follows:

H2: Altman Z' model can predict SME manufacturing company bankruptcies in Finland.

Since the Z'-model is developed almost forty years ago (1983), and the business models of manufacturing companies have changed, we will also test Altmans Z''-model which is developed for companies in the service industry. The reason behind this is that nowadays many manufacturing companies also have a lot of functions and businesses, which are comparable to services. A significant amount of manufacturing companies can provide repair and maintenance services, and possibly even consulting services. For example, the Finnish elevator manufacturer Kone, raised almost 50% of its revenue from service sales in 2017. For this reason, we can state that nowadays a significant part of manufacturing companies' revenues might come from the services. Hence, the third hypothesis is as follows:

H3: Altman Z'' model can predict SME manufacturing company bankruptcies in Finland.

In addition to these hypotheses, the study should consider the time horizon as well. It seems that the predictability of the models is significantly weakened the longer the horizon is. The Z-model accurately predicts two years prior to bankruptcy and the accuracy decreases substantially as the time horizon expands (Altman 1968). However, there is also evidence that financial ratios could reliably predict bankruptcies up to five years before bankruptcy. El Hennawy & Morris (1983) concluded that financial ratios calculated five years before the bankruptcy, gave as reliable results as those ratios calculated just one year before the bankruptcy. Thus, the fourth and last hypothesis will be formed as follows:

H4: Z -models can predict manufacturing SME bankruptcies on long term

1.3. Structure of the study

The thesis begins with a theory section. In the second chapter, the definition background of bankruptcy is discussed and reviewed. Also, the most common causes and consequences for bankruptcy are defined. This is to build a good understanding for the reader why risk awareness and bankruptcy prediction is important. The third chapter will focus preventing bankruptcy with financial analysis. The main focus of the chapter is on financial ratios and the financial statement analysis. The purpose of this is to lay down the foundation for the reader's knowledge of financial analysis and to present key financial ratios and performance metrics for company evaluation.

After a comprehensive theoretical part, previous studies will be presented and discussed. The fourth chapter aims to present the most significant studies in the topic area and to find answers to research problems. The data and methodology of the study are then presented in the fifth chapter. Finally, the results of the study are presented and compared to the initial hypotheses. The results are summarized, with conclusions, at the end of the study.

2. BANKRUPTCY & FINANCIAL DIFFICULTIES

The purpose of this chapter is to give the reader an understanding of financial problems that companies are struggling with and what are to causes and consequences for those. Also, the aim is to discuss about the concept of bankruptcy. However, the intention is not to go too deep into bankruptcy procedures and legislation. The chapter also prepares the reader for future discussion about predicting bankruptcy with financial ratios.

2.1. Definitions and background

When company's need for funding exceeds the current available amount of capital and the extra funding needed for operations cannot be achieved in a timely manner, company is momentarily insolvent. Insolvency might be just a short-term disruption and the company can recover from it. However, if the insolvency issues are not resolved, and the insolvency status takes longer, the company may become defaulted. Failing in attempts to become solvent may lead to reorganization or bankruptcy. Bankruptcy is the most serious form of corporate financial difficulties and usually results in huge losses for all stakeholders. (Laitinen & Laitinen 2004: 15-18, 65).

Bankruptcy tends to be defined as a statutory insolvency procedure whereby the debtor's entire assets are used at one time to pay off all his debts to the extent that they are enough. The aim is to ensure a fair and equitable distribution of the debtor's assets among all the creditors. The company can be declared bankrupt either on its own or at the request of its creditors. (Koulu 2004: 2; Laitinen & Laitinen 2004: 17).

Bankruptcy is in some instances used to refer to companies in financial difficulties. Some authors have used the term failed instead of bankrupt. Bankruptcy, however, is a process that begins with the company's financial problems and ends with the legal filing of bankruptcy. The exact moment of bankruptcy is difficult to determine, as the company may continue to operate for a long time even if the conditions for bankruptcy already exist. However, the time when a company or its creditors decide to file a legal action is generally considered to be a bankruptcy. (Karels & Prakash 1987).

Like mentioned, the financial difficulties of a company often precede bankruptcy. For example, inability to pay off debts is considered to be a financial difficulty and business failure. In the short term, the company may be able to continue operating despite the financial difficulties. Therefore, it is difficult to determine the point when returning to a profitable business no longer exists and bankruptcy is necessary. (Karels & Prakash 1987; Laitinen & Laitinen 2004: 15-16).

2.2. Anticipating Causes & Consequences

A company drifting into a financial crisis and bankruptcy is often due to the fact, that company or its stakeholders do not have an effective monitoring system in place to warn of an approaching crisis. If the alarming signs are noticeable early, the company and its stakeholders would have time to intervene and fix the problems. However, fixing requires a healthy foundation for business. If the company is not profitable, it’s also wise to close it as soon as possible. (Laitinen & Laitinen 2004: 19).

In most cases, financial problems have causes and consequences. Causes such, incorrect investment by the management, appear first, and it would be important to respond to them as soon as possible. However, this is often very difficult since the causes are often tough to identify and quantify. It is also impossible for an external reviewer to gain access to in-house information. As a result, most monitoring systems are based on publicly available financial statements, where the information available is the consequences. The financial information enables to build of an effective monitoring system. Even though the system based on financial information is not the most accurate and reliable, it can, at best, provide a warning many years before a potential crisis. (Laitinen & Laitinen 2004: 19-22).

Often, financial problems are reflected in the operating conditions of a company. Operating conditions can be illustrated with the health triangle shown in Figure 1. Conditions are divided into profitability, liquidity and are usually measured with financial ratios. All the operating conditions must be in order for the company to continue operating. (Laitinen & Laitinen 2004: 242-244).

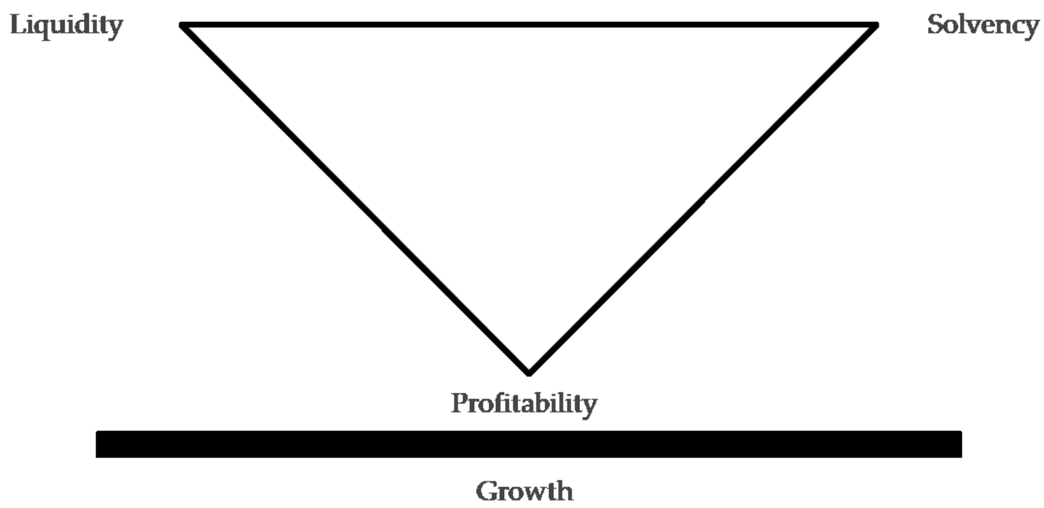


Figure 1. Health triangle of operating conditions. (Laitinen & Laitinen 2004: 243).

Of these three areas, profitability is the most important, as it relies on the business the most. This is also reflected in the figure. If a company fails to be profitable in the long run, it means that the company is making losses that constantly consumes equity. This will eventually lead to financial troubles, for example, bankruptcy.

However, good profitability alone is not enough to keep the business going. Even the company with significant profit margin may be heavily indebted or insolvent. Financial difficulties are often consequence of company’s fast growing and that the profitability is not able provide enough revenue to finance the growth. For this reason, the company might face liquidity issues. Moreover, a company in a solvency crisis may be liquid due to slow growth, but due to poor profitability it has lost its equity and might run into solvency problems. Thus, good profitability and growth play a key role in the success of a company and often “steer” the process leading to the company's financial difficulties. Below, Table 1 illustrates the relationship between growth and profitability. (Laitinen & Laitinen 2004: 242-244).

PROFITABILITY	**GROWTH**	
	Slow	**Fast**
Weak	Poor Liquidity & Solvency	Weak Liquidity & Solvency
Strong	Strong Liquidity & Solvency	Decent Liquidity & Solvency

Table 1. Impact of growth and profitability on liquidity and solvency. (Laitinen & Laitinen 2004: 265).

3. FINANCIAL ANALYSIS & RATIOS

The purpose of this chapter is to be a follow-up for previous bankruptcy and financial difficulties discussion. The objective is to introduce the definition of financial statement analysis and to provide information on the key financial ratios used in financial analysis. Thus, this chapter aims to provide a good basis for the reader before moving on to the literature review and the empirical section.

3.1. The definition of financial analysis

Financial statement analysis is an assessment of a company's financial position for decision making. In decision-making situations, financials between the years, or companies between the industries, can be compared which can help to make successful and profitable decisions. The strength of a financial analysis is therefore the comparability. Financial statement analysis can be defined to evaluate and predict financial performance of a company by using short-term financial information. (Kallunki 2011: 12; Laitinen et al. 2004: 29).

The financial statements are prepared in accordance with the principles laid down in legislation and other regulations. Indeed, accounting and financial reporting standards produce standardized financial statements that are largely comparable. (Kallunki 2011: 12.)

Financial analysis plays a key role in assessing and deciding the financial position of a company, because it reveals various dimensions of a company's financial position. It can assess, for example, a company's profitability, solvency and liquidity risks, which are essential information for decision-making. However, the challenge of financial analysis is identifying of the future success company and the future crisis company. If the company is financially stable, its usually easy to estimate it with financial ratios. However, the information produced by the forecast has minimal value in this case. The analysis only brings significant value when there is a conflict between the financial ratios and the future potential of the company. However, this conflict is hard to detect and predict. (Kallunki 2011: 13; Laitinen 2002: 41).

3.2. Adjustments

Companies can influence the content of their financial statements using different accounting policies. The purpose of these actions may be, for example, to present a lower result for tax purposes or a high enough result for the distribution of dividends. This can lead to a significantly misleading figure and make comparisons between years difficult. However, the purpose of financial analysis is to make different years and companies comparable. Thus, some adjustments for the income statement and balance sheet are needed. With adjustments it is possible to achieve a more accurate and comparable picture about the company's financial situation. Carefully and accurately adjusted income statement and balance sheet can provide significantly better forecast results. The objective on balance sheet adjustments is to obtain a true and fair view of the financial position of the company at the date of financial statement. Moreover, adjustments in income statement targets to profitability and volumes. This paper will not go further with adjustments, but there is a lot of available literature dealing with balance sheet and income statement adjustments. (Kallunki ym. 2007: 43; Yritystutkimus ry 2011: 17,31).

3.3. Financial ratios

Financial ratios are the most commonly used variables in bankruptcy prediction models (Back 2005). Financial ratio-based prediction models are typically constructed by searching through a large number of ratios whose relative weights are estimated from a sample of failed and active companies. Since the ratios and their coefficients are derived from specific sample, such models are likely to be also sample specific. (Agarwal & Taffler 2008).

In order for the bankruptcy prediction model to have good practical value, the model should be relatively straightforward to implement, the data should be easily collected and prepared, and statistically easy to test. It would also be important that the causalities between the result of the model and its variables are easily discernible and verifiable. (Jones, Johnstone and Wilson, 2017).

The information contained in the financial statements is usually presented by using financial ratios. The following ratios are presented in this chapter for measuring a company's financial position from various perspectives. The indicators have a clear economic interpretation and have good technical characteristics. These ratios are also commonly recognized in literature. In addition to these, there is a wide variety of financial ratios presented in the literature to measure the success of an enterprise and its financial position. (Kallunki 2011: 214).

3.3.1. Profitability

Profitability describes the financial performance of a business and is a prerequisite for continuing business. Profitability can be measured in absolute or relative terms. Absolute profitability is simply measured as the difference between operating income and expenses, i.e. net income. Relative profitability describes the ratio of profit and returns to invested capital, i.e. return on equity. (Yritystutkimus ry 2011: 60).

Profitability can be measured by many different variables and ways. The most common financial ratios measure how much the company has made profit in relation to invested capital or assets. Profitability can be measured by the following ratios:

(1) $$\text{Net income } - \% = \frac{\text{Net income}}{\text{Revenue}} \times 100$$

In order to be a profitable company, company's net income must be positive. It should be noted that this ratio doesn't take company's financial structure into account. (Yritystutkimus ry 2011: 62).

(2) $$\text{Return on Assets } - \% \text{ (ROA) } = \frac{\text{Net income}}{\text{Average Total Assets}} \times 100$$

Return on assets measures the company's ability to generate return with all the company's assets. This indicator is more useful than ROI when the distribution of interest-bearing and non-interest-bearing capital cannot be determined. (Yritystutkimus ry 2011: 63-64).

(3) $$\text{Return on Investment } - \% \text{ (ROI) } = \frac{\text{Net income}}{\text{Capital Employed}} \times 100$$

Return on investment measures the relative profitability. It is the return on invested capital that requires interest or other returns. The comparability of the ratio between different companies may be impaired by the lack of sufficient data to allocate debt to interest-bearing and non-interest-bearing capital. Large investments and appreciations may also complicate the evaluation of the ratio. (Yritystutkimus ry 2011: 64-65).

(4) $$\text{Return on Equity} - \% \text{ (ROE)} = \frac{\text{Net income}}{\text{Average shareholders' Equity}} \times 100$$

Ratio measures of a company's ability to add value to its owners and the capital they invest in the company. The target level for ROE is determined by the shareholders required rate of return, which is substantially affected by the investment risk. Possible appreciations have a significant impact on this ratio. (Yritystutkimus ry 2011: 65).

3.3.2. Solvency

The company's capital structure plays a key role in measuring a company's solvency. There are a several key indicators that can provide a comprehensive understanding of a company's solvency:

(5) $$\text{Solvency ratio} - \% = \frac{\text{Shareholders' Equity}}{\text{Total Assets} - \text{Advances received}} \times 100$$

Ratio measures a company's solvency, its ability to withstand losses, and its ability to meet its long-term commitments. It describes the owners share of assets in the total financing of the company. The more the financing is done with equity, the better the chances for the company to cope with the costs of using debt. Also, it is important to notice that if appreciations have been made, comparability between years is affected. Solvency ratio of more than 40% is good and less than 20% is correspondingly weak. (Yritystutkimus ry 2011: 66).

(6) $$\text{Gearing} - \% = \frac{\text{Non current liabilities} - \text{Cash and cash equivalents}}{\text{Shareholders' Equity}} \times 100$$

In numerator of the ratio is the amount of debt that should in principle be interest-bearing. When gearing is under 100% it can be considered as good. Moreover, company might have weak solvency ratio but good gearing if it has a lot of debt but also a lot of available cash. (Yritystutkimus ry 2011: 68).

3.3.3. Liquidity

Liquidity refers to the ability of a company to handle all its payments on time. Taking advantage of cash discounts can usually indicate good liquidity, while overdue payments and interest paid are a sign of weak liquidity. Liquidity can be dynamic or static. Dynamic liquidity measures the sufficiency of cash flow to meet the payment obligations during the financial year. From a static point of view, liquidity is viewed at a given point in time, as at the financial statement date. In this case, the amount of the most liquid assets are compared to current liabilities. (Yritystutkimus ry 2011: 71).

The following liquidity ratios are both static liquidity ratios and measure the situation at the closing date of financial statement:

(7) $$\text{Quick ratio} = \frac{\text{Current Assets} - \text{Inventory} - \text{Prepaid expenses}}{\text{Current Liabilities}}$$

Quick ratio measures the ability of a company to meet its current liabilities with financial assets alone. Only the financial assets are estimated to be of value in the event of the firm being wound up and its assets sold. If the ratio is between 0,5 and 1 it can be said that the liquidity of the company is satisfactory. (Yritystutkimus ry 2011: 71).

$$(8) \qquad \text{Current ratio} = \frac{\text{Current Assets}}{\text{Current Liabilities}}$$

In current ratio, the time horizon is a bit longer. The ratio will also take inventories into account and assumes that inventories could also be realized to meet short-term obligations. The value of inventories is difficult to estimate and, therefore, current ratio is rarely used alone to assess a company's liquidity. If the ratio is between 1 and 2 it can be said that the liquidity of the company is satisfactory. (Yritystutkimus ry 2011: 71-72).

3.3.4. Efficiency

The last part of the key financial ratios is efficiency, which is usually used alongside of liquidity. This is because the level of liquidity is affected by the sufficiency of the cash flow. Also, the sufficiency of cash flow is influenced by the accruals of income and expenses incurred, which are measured with efficiency ratios.
An efficiency ratio measures the ability of a company to use funds to generate profit. Efficiency ratios are important, because an improvement in the efficiency ratio usually results to improved profitability. The most common performance ratios are collection period and credit period times which describe how long it

takes a company to generate sales revenue and pay purchase invoices. (Kallunki 2014: 128–130).

(9) $$\text{Collection period (days)} = \frac{\text{Debtors}}{\text{Operating revenue}} \times 365$$

(10) $$\text{Credit period (days)} = \frac{\text{Creditors}}{\text{Operating revenue}} \times 365$$

4. LITERATURE REVIEW

4.1. Background

There has been a lot of research in predicting bankruptcy and there is a considerable amount of different results. New, better and more accurate methods are constantly being developed to predict bankruptcy. However, it seems like in most cases the methods are based on financial ratios like inefficiency, high leverage and poor liquidity. (Back 2005).

Although many of the studies have developed prediction models for the bankruptcy by using variety of statistical techniques, still a significant part of the studies has employed US data to extend and Beaver's (1966) univariate methodology and Altman's (1968) multiple discriminant analysis model (Muscettola 2015). Hence, in the literature review section, this paper is having a special focus and more detailed discussion about these studies.

In this section the aim is to find out the most important financial indicators for predicting bankruptcy by using existing literature. The section also attempts to perceive the best research methods and get answers to the research problems by going through and examining some of the best-known researches in the field of default prediction, starting from the previously mentioned classics.

Beaver (1966) was the first to bring something clearly new and different to bankruptcy predicting by developing a univariate model which focused on exploring the ability of individual key figures to predict bankruptcies. This industry classic study included 158 companies divided into two groups, bankrupt and non-bankrupt. Beaver found significant differences between the financial ratios of these two counterparty groups. Beaver's research was an important academic advancement because, according to its results, a warning about an impending crisis is available at an early stage. Also, the methodology of the study can be easily applied in the practical businesses. However, weakness of the forecasting model based on individual ratios is the ambiguity of the results given by it, since different indicators can give different forecasts to the same company. Also, single ratio does not necessarily contain all the essential information about the state of the company because the information could be divided between the several key ratios.

In his study, Beaver stated that a possible multi ratio model is more accurate for predicting bankruptcy than just individual financial ratios. The development of a single variable analysis to a multivariable analysis was an important motivation for the further research. Edward Altman was the first researcher who went on to develop this model.

4.2. Classic Z-score models

Many studies have concluded that the financial ratios calculated from the financial statements of bankruptcy companies differ significantly from those of non-bankruptcy companies (Altman 1968). Financial information and financial ratios acquired from the financial statements are not always satisfied, as they seem to give a very unilateral and bias picture of the company's financial situation. However, this is often due to the inability to utilize the information correctly. Attention should not be paid only to the values of individual financial ratios, but to look at the company's financial statement as a whole. It is not possible to get a reliable picture of a company's success by looking at, for example, a single key indicator of profitability, because then the overall picture will be weak and dependent only on that variable. This might cause some possible distortion in interpretation. The most realistic perspective is obtained by looking at several different factors in financial statements together, analyzing the ratios and numbers, and comparing the results, for example, with other companies. (Taffler 1983).

Altman (1968) criticizes the ability of one variable to describe a company's financial situation because it does not consider all the company's operating conditions. For example, if a company has poor profitability, it is considered a potential bankruptcy company, but in case company has good liquidity ratios the situation might be considered different. Thus, Altman's vision was to build a single predictable model with many financial ratios included.

4.2.1. Z-Model for public firms

Altman's (1968) research can be considered one of the most groundbreaking researches in the field of bankruptcy forecasting. It was first of its kind to use multiple discriminant analysis (MDA) for predicting corporate bankruptcies. The advantage of the MDA is that it utilizes more information at the same time by using multiple variables. In his study, the original sample included a total of 66 manufacturing companies from 1946 to 1965 divided in to two groups, bankrupt group and non-bankrupt group. According to Altman, the time period of the study was not ideal, as the averages of the ratios change considerably over such a long period of time. However, due to the lack of data accessability it was necessary to use the information available. Long time interval could have affected the results of the study.

The data for the study is collected from the balance sheets and income statements. Previous studies have shown that many financial variables are significant in predicting the financial problems of companies, thus Altman formed a list of 22 potentially helpful ratios for evaluation. He divided these ratios in to five categories; liquidity, profitability, leverage, solvency and activity ratios. The criteria for selecting these 22 ratios were the popularity in the literature and the potential relevancy for research. From the original list of 22 variables he finally selected five different variables. Altman did not choose the most significant variables measured independently because the selection was based on the ability of the variables to do best overall job together and form the best bankruptcy prediction model. (Altman 1968).

The purpose of the Altman's model is to find out the ideal combination of different financial variables that best predict bankruptcies and then combine these together into a single weighted index which defines the company's probability of default. Altman named this index as Z-score. The formula developed by Altman below:

(11) $$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5.$$

where,

X_1 = Working Capital / Total Assets (Liquidity indicator)

X_2 = Retained Earnings / Total Assets (Profitability indicator)

X_3 = Earnings before interest and taxes / Total Assets (Profitability indicator)

X_4 = Market value equity / Total liabilities (Solvency indicator)

X_5 = Sales / Total Assets (Efficiency indicator, Asset turnover)

Z = Overall Index

To summarize, Z-Score combines liquidity, profitability, solvency and efficiency ratios to draw a conclusion about the overall score. The higher the value of the z-score, the less likely it is that the company will face bankruptcy.

Altman defined a critical value for the results. Companies with a score over 2,99 were functional and in the "safe zone" and companies with a score below 1.81 were considered as bankruptcy. Hence, if the result score is over 2.99, the model would correctly classify all companies as healthy and if the score is 1.81 or less, would the model correctly classify the company to bankrupt sector. Area between these two critical values is the so-called "gray area". In this area, the model cannot fully predict the outcome and classification errors occur.

After testing the discriminant analysis model Altman concluded that the model is an accurate forecaster of failure with 95 per cent of the companies were assigned to their actual group classification. Furthermore, the function was accurate in several other samples where reliability was tested. However, the predictive power differs between time horizons. The model accurately predicts two years prior to bankruptcy and the accuracy decreases substantially as the time horizon expands.

4.2.2. Z'-Model for private firms

Altman (1983) further developed his research and customized the model for small unlisted companies. He re-estimated the original coefficients for the variables and the market value of equity he replaced with the book value. As the original Z-model used market value, it could not be used for non-public companies. Altman therefore replaced the market value with the book value and re-estimated the coefficients of the ratios. This model is known as Z'. The Z'-model is used to determine the bankruptcy potential of manufacturing companies. Below the model and the variables are presented:

(12) $Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5.$

where,

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings before interest and taxes / Total Assets

X_4 = Book value of equity / Total Liabilities

X_5 = Sales / Total Assets

4.2.3. Z''- Model for service companies

Altman (1983) also developed a Z''-model which is estimated for non-manufacturing firms. This study aims to predict bankruptcy in manufacturing companies. However, the classification accuracy of the Z''-model will be also examined since the structure of the manufacturing companies makes it a considerable idea.

The asset turnover ratio (Sales / Total Assets), X_5 variable, has been completely removed from the model since it is industry specific variable. Z-score estimated for non-manufacturers below:

(13) $Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$

where,

X_1 = Working Capital / Total Assets

X_2 = Retained Earnings / Total Assets

X_3 = Earnings before interest and taxes / Total Assets

X_4 = Book value of equity / Total Liabilities

4.3. Literature related to bankruptcy prediction

Over the past few decades, many studies have focused on finding the best possible method of predicting bankruptcy as accurate bankruptcy predictions benefit both academic researchers and industrial companies. Many studies have attempted to develop the most effective statistical model for predicting bankruptcy. However, it should be noted that although those classic statistical methods developed by Altman (1968, 1983) and Beaver (1966) are still popular, some problems have also been identified in them. (Shumway 2001; Balcaen & Ooghe 2006). However, it is good to emphasize that most of the methods for predicting bankruptcy are still based on financial ratios (Back 2005).

James A. Ohlson (1980) developed one of the first bankruptcy models based on logistic regression. Although logistic regression had been developed 70 years earlier, it had not yet been applied to bankruptcy prediction. This method eliminated the limitations and assumptions of multivariate analysis, so that, for example, dummy values could also be used as explanatory variables. Ohlson criticizes Altman's original (1968) study for overestimating the model's ability to predict bankruptcy. This is because there is data from the financial statements published after the bankruptcy and the predictive power of the model increases because bankruptcy is then "easier" to predict. In response to restrictions of linear discriminant analysis (LDA) Ohlson presented the O-score.

In his study, Ohlson (1980) includes nine different financial ratios that he analyze using the logistic regression method. The sample size is significantly larger compared to Altman's study since the sample consists over 2000 companies. He finds that the most suitable ratios to predict bankruptcy is the company's gearing and some of the key indicators of profitability and liquidity. According to the research, the size of the company also has a negative effect on the probability of default. The larger the company, the less likely it is to go bankrupt. The O-Score was found to be 70% accurate within 2-year period before bankruptcy.

The difference in why Ohlson's model predicted bankruptcy with weaker results than Altman's (1968) can be explained, among other things, by the much larger amount of companies in Ohlson's sample. Altman's data (66 companies) can be considered small, and the matching pair process can also influence the outcome. Later, for example, Laitinen and Kankaanpää (1999) experimented different predicting models for the Finnish material, and the logit model performed better than the linear discriminant model. On average, the classification accuracy for log-models has been 87%, which is slightly better than LDA with 85% accuracy (Aziz & Dar 2006).

Hillegeist, Keating, Cram and Lundstedt (2004) study whether the two popular accounting information-based models, the Altman Z-score and Ohlson O-score, make effective use of publicly available information in bankruptcy prediction. They compare the relative data content of these scores to a market-based bankruptcy prediction model developed using the Black-Scholes-Merton (BSM) option pricing model. They find that BSM-based model can provide significantly more accurate information than either of the accounting-based models. This observation is robust to various modifications of the Z-Score and the O-Score, including updating the coefficients and industrial adjustments.

Li (2012) studied the predictability of bankruptcy in the United States, utilizing the z-score developed by Altman which was originally meant for manufacturing companies. The study focused on non-manufacturing companies and concluded that even though the sample didn’t consist any manufacturing company, nevertheless, the model worked well. Although it has been developed many new methods over the years for bankruptcy prediction, it seems, however, that the method developed by Altman (1968) is still capable of providing reliable and accurate results.

Casey's (1980) study finds that the best indicator for predicting bankruptcy is gearing. In addition, he also found the current ratio and the return on assets (ROA) as a strong explanatory factor. Based on some of the above-mentioned studies, the solvency ratios would therefore be the most accurate forecasters, followed by indicators of liquidity and profitability.

Lugovskaya (2009) investigated the prediction of bankruptcies of Russian SMEs, utilizing financial ratios in the analysis. She chose the list of different financial ratios and tried to find out if they could predict the bankruptcy of Russian SMEs reliably. She applied a multivariable model to Russian SMEs bankruptcy prediction. A comprehensive list of variables including profitability, liquidity and efficiency ratios was chosen as the to be analyzed. Based on statistical analyzes, the best indicators of bankruptcy in Russian SMEs turned out to be liquidity indicators. The most significant results were obtained by calculating the debt coverage and the structure of assets in the company. Moreover, Lugoyskava found that profitability ratios were also significant, especially return on equity (ROE) proved to be a good predictor of bankruptcy. However, it is noteworthy that the solvency ratios were not included in the model under study.

Other studies have also surprised with more than 90% predictive accuracy. Appiah & Abor (2009) investigates the predictability of bankruptcy in the Great Britain with industrial companies. In their research, they use multivariable analysis and include variables that were previously found good and suitable predictors in the literature. The results show that the industrial bankruptcies could be predicted using financial ratios with great accuracy and reliability.

Jones & Hensher (2004) study bankruptcy forecasting in Australia with mixed logit model. They include four different industries in their sample and predict company defaults by using financial indicators. The model include seven different financial ratios, representing liquidity, solvency, profitability and efficiency. The ratios are calculated from one to five years prior to the financial statements published at the time of the bankruptcy. These ratios, derived from the financial statements of the companies, give really reliable results on the probability of default in all four sectors.

Pompe and Bilderbeek (2005) study the predictability of bankruptcy of Belgian SMEs also by using financial ratios. A total number of 73 different key financial variables were included in the study, which they finally ended up using 43. In addition to the large number of financial indicators, the survey included almost 1,400 Belgian bankruptcy companies whose financial statements were reviewed for a period of five years. The study shows that each of the financial ratios have even some significance in the company's bankruptcy. However, solvency ratios were the most successful and significant.

When using financial ratio analysis for predicting bankruptcy, it should be noted, that some ratios are more suitable for short-term and some for long-term. For example, profitability indicators may potentially predict bankruptcy for up to five years before the event, while liquidity indicators perform poorly in such a long term. Liquidity is a good measure in the short term, and it can provide reliable results one or two years before bankruptcy. (Beaver 1966).

Pompe and Bilderbeek (2005) also investigate whether other financial ratios predict bankruptcy earlier than others. They expect that profitability and efficiency indicators would be the earliest warning indicators of a bankruptcy and liquidity would be the most significant in real close to the bankruptcy. However, the study did not find any statistical evidence for this hypothesis. Thus, all the ratios turned out to be at least somewhat significant and no reliable results were found for temporal predicting ability.

On the other hand, there is also evidence that financial ratios could reliably predict bankruptcies up to five years before bankruptcy. Lugoyskava (2009) is able to predict corporate bankruptcies with financial and a few non-financial variables for up to five years before the bankruptcy itself, almost with eighty-percent probability. Furthermore, El Hennawy & Morris (1983) conclude that financial ratios calculated five years before the bankruptcy, give as reliable results as those ratios calculated just one year before the bankruptcy. This is a useful and significant result in terms of the fact that such an early warning on the threat of bankruptcy would surely be of great benefit to the various stakeholders than only the information obtained a year earlier. The conclusion of the study is that the best indicators of bankruptcy, both five and one year before bankruptcy, turns out to be profitability indicators. (El Hennawy & Morris 1983). Thus, based on this study, bankruptcies could be predicted with financial indicators reliably up to five years before bankruptcy.

Results discussed above create confidence for the hypothesis of this study, as predicting seems to be possible in the longer term as well. Also, in general, financial ratios seem to have strong predicting power for company bankruptcy. This is good news for the hypotheses of this study.

Karels and Prakash (1987) bring together the key financials used in previous studies that has been proved to be working. The dispersion of these financials is high, as the list contains up to 30 different financial ratios. These financials comprehensively represent different types of financial ratios, as there are many ratios on profitability, liquidity and solvency. The theoretical basis for selecting financial ratios is rather limited, so the high dispersion of the ratios is not surprising.

Smith and Liou (2007) investigate bankruptcy prediction in manufacturing industry. The research includes financial ratios acquired from the companies' financial statements that comprehensively represented different types of areas. The choice of these ratios is justified by the fact that the ratios have been popular in previous studies and in this way have proven to work.

Back (2005) examines the financial variable and non-financial variable impact on the likelihood of bankruptcy in Finnish companies. In his study, he ends up with the fact that the company's debt is positively correlated with the probability of bankruptcy, i.e. the more indebted the company, the more likely it is to go bankrupt. However, the financial ratios for profitability did not prove to be relevant in predicting bankruptcy. On the other hand, a survey conducted a few years earlier conclus that both gearing and profitability indicators are the best predictors of bankruptcy (Shumway 2001). It seems that often the solvency ratios have worked well as predictors of bankruptcy and, depending on the research, liquidity or profitability indicators have also proved to be relevant.

5. DATA & METHODOLOGY

In the theory part of this thesis, financial ratio analysis is examined, with the help of previous literature. The focus is on bankruptcy prediction with financial ratios. Moreover, the purpose of this study is to examine the bankruptcy predictability with Altman Z-models. The functionality of the models is tested with SME manufacturing companies from Finland. It would be interesting to see, whether the Z-models created in early 1980s can predict today's global and flexible companies. This chapter provides an overview of the selected data, as well as an overview of the research methods used.

5.1. Data

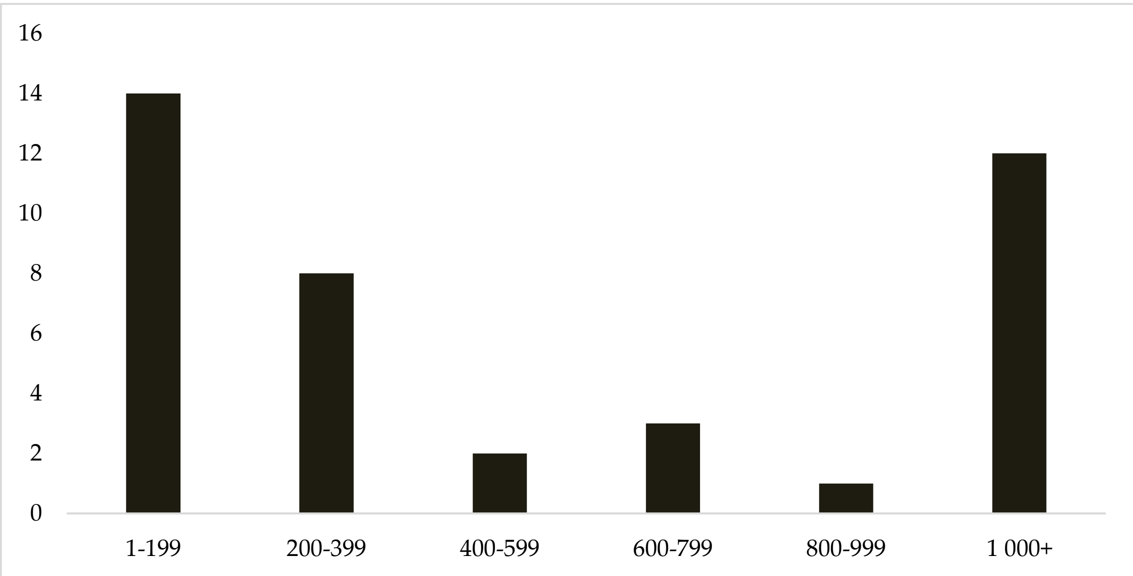
All the data needed to carry out the study was obtained from the Bureau van Dijk's Orbis database (BvD). BvD is an analytics company owned by Moody's. Orbis contains information from millions of companies worldwide. It is possible to search for information using different kind of filtering criteria. There is a very wide range of criteria available, such as geographical location, financial information, industry classification and many more.

Orbis has the ability to obtain pre-calculated financial ratios from the companies' financial statements. However, this feature was not useful for this study because the ratios provided by the database are not included in the Altman Z-model. The financial ratios have therefore been calculated from the financial statements using Excel spreadsheet. The financial statements used in the study are from 2013 to 2018.

Bankrupt companies were searched from Orbis by limiting the search to Finnish manufacturing companies whose bankruptcy status had been in effect since the beginning of 2018. The requirement was also that the financial data should be available for the last five years and the company should be a private limited company.

A total of 44 companies were found by using the above criteria and all of the companies were SME sized. However, four companies with deficient financial information were excluded from the dataset so that the final bankrupt sample consisted 40 companies. Twenty-four companies had issued a bankrupt status in 2018 and sixteen companies in 2019. The mean asset size of these companies is 1,3M€ with the range from 5 000€ to 10,4M€. Figure 2 illustrates the size distribution in bankrupt sample.

Figure 2. Size distribution by Total Assets (th. EUR).



The bankrupt sample is quite evenly distributed across companies of all sizes. However, the largest quantities are in micro and large classes. Since all the sample companies were manufacturing companies, the industrial distribution is presented by subcategory level in Table 2.

Table 2. Industry Distribution by NACE code.

Industry (NACE Group)	**Count**	**Per cent**
Computer, electronic and optical products	1	3 %
Electrical equipment	2	5 %
Fabricated metal products	10	25 %
Food Products	2	5 %
Furniture	2	5 %
Leather and related products	1	3 %
Machinery and equipment	3	8 %
Other Manufacturing	2	5 %
Other transport equipment	3	8 %
Printing and reproduction of recorded media	3	8 %
Repair and installation of machinery and equipment	1	3 %
Rubber and plastic products	3	8 %
Wearing apparel	2	5 %
Wood and products of wood	5	13 %
Total	**40**	**100 %**

A quarter of the sample companies are manufacturing fabricated metals. Furthermore, companies manufacturing wood and products of wood make up significant portion (13%), while rest of the sample is evenly distributed across the industries.

Orbis was also used for searching the active companies for matching counterparties to bankrupt companies. The active, non-bankrupt, companies were restricted to Finnish manufacturing companies, whose status in the database was active at the beginning of 2018. These firms were also required to have financial statements available for the previous five years. Finally, the search was limited to companies with total assets below 11M€. The decision to eliminate the companies above 11M€ in total assets is due to the asset range of the firms in bankrupt group. For example, Altman (1968) used this paired sample selection method.

The non-bankrupt sample first consisted 6364 companies. However, all the companies with deficient financial information were excluded together with companies that had compliance sanctions flags. After these exclusions, non-bankrupt sample contained 5510 companies. The final sample of 40 active companies were chosen on a stratified random basis to consist a paired sample with the bankrupt companies, increasing the whole sample size to 80 companies.

5.2. Methodology

This study examines the developed versions of the Altman (1983) models that are suitable for classifying private limited companies between bankruptcy and active companies. These models are called Z' and Z''-models. Although Hillegeist et.al. (2004) note that the accuracy of the Altman Z-score, based on accounting information, is weaker than the market-based model; Given that the research sample is mainly composed of non-publicly listed SMEs, the market-based model could not be used.

The Z'-model is used to determine the risk of bankruptcy for non-public manufacturing companies and Z′′-model for non-public non-manufacturing companies. Although the sample only includes manufacturing companies, we also want to look at the power of Z′′-model, since modern manufacturing companies have a lot of service-like businesses such as maintenance and repair. The variables, models and zones of discrimination for Altman Z′ and Z′′ (1983) are presented below.

Table 3. Definition of financial ratios.

Variable	Definition
X_1	Working Capital / Total Assets
X_2	Retained earnings / Total Assets
X_3	Earnings before interest and taxes / Total Assets
X_4	Book Value of Equity / Total Liabilities
X_5	Sales / Total Assets

(14) $$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5$$

Zones of discrimination:

Safe zone: $Z' > 2,90$

Grey zone: $1,23 \leq Z' \leq 2,90$

Distress zone: $Z' < 1,23$

(15) $$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Zones of discrimination:

Safe zone: $Z'' > 2,60$

Grey zone: $1,10 \leq Z'' \leq 2,60$

Distress zone: $Z'' < 1,10$

These models use the same information provided by the same financial ratios (Table 3). However, the Z′′-model leaves the asset turnover ratio (X_5) out of the scope since it is not essential for non-manufacturing companies and the ratio is often industry specific. (Altman 1983).

The Z-models considered in the study do not have a single critical point that distinguishes between active and bankrupt companies. Instead, there is a so-called "gray area" between them, which poses challenges for defining a classification. When the company's score is in this gray area, the model is not sure in which category this company belongs to. Thus, the gray area is the uncertainty area of the Z-model.

In this research the functionality of the Altman model is examined with new, up to date, Finnish data, and thus no attempt is made to find new financial indicators that might increase the accuracies of Altman's Z-models. The accuracies of the Z-models are calculated for one, two and five years before bankruptcy. This provides a broad understanding of the models' ability to predict in short- and long-term. Moreover, these abilities of Altman models to classify companies to safe and distress zones are compared. The analysis has performed by using Excel spreadsheet and data analysis toolpak.

In the study, total error classifications are divided into categories; gray and wrong. Gray category includes all the companies that the model is not able to classify. Wrong category includes all the companies that the model classifies wrong. Furthermore, wrong category is divided into Type I and Type II errors, depending on how the classification error occurs. If the bankruptcy company is classified as an active (Type I classification error) or an active company is classified as a bankrupt (Type II classification error).

6. EMPIRICAL RESULTS

This chapter presents the empirical findings of the study. The beginning of the chapter examines whether there are differences in the financial ratios of an active and a bankrupt company. This assumption of differences has served as the basis for bankruptcy prediction studies. After that, the classifications of the Z-models are presented with the data described in previous chapter.

6.1. Financial ratio distribution and F-Test

To examine whether there is difference between financials in bankrupt group and active group, an F-test is carried out. This test also provides valuable information about the individual classification ability of the variables since the results show the most significant variables for the model. Table 4 presents the variable means one financial statement year prior to bankruptcy and the resulting F-ratios.

Table 4. Variable means and test of significance (Year 1).

Variable	Bankrupt Mean	Active Mean	F-Ratio
	n = 40	*n = 40*	
X_1	-77,0 %	28,4 %	14,04*
X_2	-128,7 %	25,8 %	15,42*
X_3	-37,5 %	11,5 %	17,44*
X_4	-14,0 %	482,6 %	14,34*
X_5	296,1 %	187,8 %	1,91

* Significant at the 0,01 level.

$F_{1,80}\ (0{,}01) = 6{,}96$

$F_{1,80}\ (0{,}05) = 3{,}96$

Variables X_1 to X_4 are all significant at the 0,01 level. This indicates extremely significant differences in these financials between bankrupt and active groups. It is also surprising to see how evenly all the variables are affecting to model. However, variable X_5 seems to be insignificant in univariate basis.

This finding is also supporting the fact that Altman has included these variables into the models. Altman (1968) found that X_5 variable is not significant at the univariate level but it is significant at the multivariate level due to negative correlations between the variables.

It is also good to look at the differences between the variables in the longer term. Variable means two financial statement year prior to bankruptcy and the resulting F-ratios are presented in Table 5.

Table 5. Variable means and test of significance (Year 2).

Variable	Bankrupt Mean	Active Mean	F-Ratio
	n = 40	*n = 40*	
X_1	-13,9 %	23,0 %	7,04*
X_2	-44,3 %	18,4 %	8,51*
X_3	-18,1 %	11,0 %	25,74*
X_4	5,1 %	331,1 %	12,06*
X_5	208,9 %	188,7 %	0,31

* Significant at the 0,01 level.

$F_{1,80}\ (0{,}01) = 6{,}96$

$F_{1,80}\ (0{,}05) = 3{,}96$

From table 5 it can be seen that for all X_1-X_4 variables, the F-ratio is highly significant at the 0,01 level. X_3 is the most significant variable in the set. The values of bankrupt companies are still clearly negative and those of active companies are positive. From this it can be concluded that all these variables are still significant in the model even though the period under review is longer. The only difference is the variable X_5 which seems to be insignificant again.

Finally, to understand the predictive power of the model over the long term, we look at the differences in variables five years before the status horizon. Variable means five financial statement year prior to bankruptcy and the resulting F-ratios in Table 6 below.

Table 6. Variable means and test of significance (Year 5).

Variable	Bankrupt Mean	Active Mean	F-Ratio
	n = 40	*n = 40*	
X_1	1,2 %	26,5 %	9,07*
X_2	-24,6 %	25,5 %	2,89
X_3	-4,0 %	5,8 %	1,48
X_4	34,0 %	219,8 %	10,29*
X_5	199,2 %	216,0 %	0,15

* Significant at the 0,01 level.

$F1,80\ (0,01) = 6,96$

$F1,80\ (0,05) = 3,96$

Variable X_1 and X_4 are still significant at the 0,01 level while the rest become insignificant. Thus, it can be concluded that the biggest differences in bankruptcy and active company ratios are in variables X_1 and X_4. Moreover, interesting note is that variable X_3 is no longer significant even though it was clearly the most significant 2 years before bankruptcy. To summarize, the ratios are clearly different for bankruptcy companies and active companies. Also, as expected, the difference between all financial variables narrows the longer the time horizon is.

The empirical part continues with a closer look at the ability of Altman Z-models to classify bankrupt and active companies correctly. For each company in the data, a Z-score was calculated and compared to the critical points of the model to obtain a classification result.

6.2. Predicting power of Altman Z′-Model

The classification of the Z′-model is examined first among bankruptcy firms and then among active firms. The overall accuracy capability of the model is introduced in the end. Table 7 reports the accuracy of Altman Z′ in bankrupt group. Correct classification means model has predicted the bankruptcy by classifying the company into a distress zone. Gray area means that the Z′-model couldn't classify the company. Wrong classification means that error has occurred, and company has been assessed for safe zone instead of distress zone.

Table 7. Altman Z'- model's predicting accuracy in *Bankrupt Group*.

Bankrupt Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	25	18	18
Gray area	9	14	11
Wrong classification	6	8	11
(Total)	*(40)*	*(40)*	*(40)*
Accuracy per cent	63 %	45 %	45 %

The results show that during the first year the model is able to classify bankruptcy companies correctly with reasonable accuracy (63%). When looking at the classification accuracy for a longer period of time, the model is not able to classify even a half of the companies correctly (45% in both 2 and 5 years). This trend reflects the results of previous studies that the accuracy is getting weaker moving further away from bankruptcy year. However, the poor accuracy in second year was a somehow surprising result.

Before reaching for larger conclusions, let's have look at how the model classifies active companies. Classification results for active group is presented below in table 8.

Table 8. Altman Z'- model's predicting accuracy in *Active Group*.

Active Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	25	23	23
Grey area	11	14	13
Wrong classification	4	3	4
(Total)	*(40)*	*(40)*	*(40)*
Accuracy per cent	63 %	58 %	58 %

Overall, the classification results for active companies are just about better than for bankruptcy companies. One year before bankrupt, model classifies active companies equally well as bankrupt companies (63%). In longer term, the classification accuracy is slightly better (58% vs. 45%) for active companies than bankrupt companies. However, based on previous literature, the accuracy is still worse than expected.

Table 9 shows results for the whole dataset. As previously stated, the classification results are not as expected. One year prior, the model is able predict bankruptcies with accuracy of 63%. As soon as the time horizon is longer, the added value is lost, since the accuracy is almost equal to random choice or a coin flip. This significance is also shown by the p-value, which has been tested with one sample t test. The one year prior to bankruptcy is the only significant accuracy compared to random choice (50%). Also, it is interesting to note that most of the poor accuracy of the model is due to the gray area. Furthermore, misclassifications are mainly due to the classification of bankrupt company as active companies.

Table 9. Altman Z′ model predicting accuracy in whole dataset.

Whole Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	**50**	**41**	**41**
Bankrupt	*(25)*	*(18)*	*(18)*
Active	*(25)*	*(23)*	*(23)*
Grey area	**20**	**28**	**24**
Bankrupt	*(9)*	*(14)*	*(11)*
Active	*(11)*	*(14)*	*(13)*
Wrong classification	**10**	**11**	**15**
Bankrupt (Type I)	*(6)*	*(8)*	*(11)*
Active (Type II)	*(4)*	*(3)*	*(4)*
Total	80	80	80
Accuracy per cent	**63 %**	**51 %**	**51%**
P-Value	0,01*	0,41	0,41

Significant at 0,05 level *

Overall, the Z'-model should be the model developed for manufacturing companies. Based on the results obtained, the functionality of the model in modern manufacturing companies can be questioned. The model was developed a long time ago when companies were structured and operating differently than today. Nowadays, global manufacturing companies provide a lot of services along with their core operations, and this can be a significant reason why the model is not able in being so accurate anymore.

6.3. Predicting power of Altman Z′′ Model

Next, let's look at Altman's Z''-model, which ignores asset turnover (X_5) and thus, is better suited for non-manufacturing companies. Given the nature of today's manufacturing companies, it is exciting to see how this model can predict bankruptcies also in manufacturing group. Table 10 below, shows the classification results for bankrupt group.

Table 10. Altman Z′′- model's predicting accuracy in *Bankrupt Group*.

Bankrupt Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	33	29	22
Grey area	1	6	10
Wrong classification	6	5	8
(Total)	*(40)*	*(40)*	*(40)*
Accuracy per cent	83 %	73 %	55 %

The Z''-model can classify bankruptcy companies correctly with 83% accuracy one year prior to bankruptcy. This result can be considered excellent and in line with previous literature. Even two years before bankruptcy, the model is still providing clear added value with its accuracy of 73%. However, it is noticeable that in the long run (5 years) the accuracy of the model is significantly reduced.

Above results in bankruptcy group are promising when compared to the previous Z'-model. Below, in table 11, are the results from the active group.

Table 11. Altman Z′′-model's predicting accuracy in *Active Group*.

Active Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	29	28	28
Grey area	5	6	4
Wrong classification	6	6	8
(Total)	*(40)*	*(40)*	*(40)*
Accuracy per cent	73 %	70 %	70 %

Moreover, these results can also reveal the high accuracy of the Z′′-model. The results show that during the first year, the model is able to classify active companies correctly with an accuracy of 73%. Surprisingly, the accuracy of the model does not diminish by much in the active group as the time horizon increases. The model accuracy is still at a good level (70%) 5 years before bankruptcy.

Finally, table 12 shows the results for Z′′-model discrimination accuracy using the whole dataset. The results are significantly better than the ones obtained with the Z′-model. In the first year, the Z′′-model can predict bankruptcy with the accuracy of 78%. Two years before bankruptcy the accuracy is 71% and five years before 63%. The gray area in the model is significantly smaller than in the Z'-model. One year before the bankruptcy, the model classified only 6 (7,5%) companies in the gray area. Classification errors were also distributed evenly to Type I and Type II in each year.

Table 12. Altman Z''- model's predicting accuracy in whole dataset.

Whole Group	Years Prior to Bankruptcy		
	1	**2**	**5**
Correct classification	**62**	**57**	**50**
Bankrupt	*(33)*	*(29)*	*(22)*
Active	*(29)*	*(28)*	*(28)*
Grey area	**6**	**12**	**14**
Bankrupt	*(1)*	*(6)*	*(10)*
Active	*(5)*	*(6)*	*(4)*
Wrong classification	**12**	**11**	**16**
Bankrupt (Type I)	*(6)*	*(5)*	*(8)*
Active (Type II)	*(6)*	*(6)*	*(8)*
Total	80	80	80
Accuracy per cent	**78 %**	**71 %**	**63 %**
P-Value	0,00**	0,00**	0,01*

Significant at 0,01 level **

Significant at 0,05 level *

Even though the Z''-model cannot achieve as good results as in previous studies, it can be stated, that the model can provide significant added value when predicting bankruptcy in Finnish manufacturing companies. Accuracy comparison to coinflip (50%) is significant in both short- and long-term, being highly significant two years prior to bankruptcy. In general, the Altman's Z''-model is still able to classify between active and bankruptcy companies in the last two years before bankruptcy. If the time period increases, the classification results can no longer be considered such trustworthy that the model would be a reliable long-term bankruptcy predictor. The results prove that it still has the capacity for classification results and it is worth using and developing.

7. CONCLUSIONS

The purpose of this thesis was to examine the predictability of bankruptcy of Altman Z models in a most recent data sample of Finnish manufacturing companies. The Z-models used in the study were two models developed by Altman and designed for non-publicly traded companies. One of the models is meant for manufacturing companies and the other for service companies.

The thesis consisted a theoretical and empirical part. In the theoretical part, the most important financial categories and the most commonly known financial ratios were introduced. In addition, the definition of bankruptcy was reviewed, and the causes and consequences of bankruptcy were discussed. The theory section also focused on previous literature. The foundations and development of the Altman Z-model were a significant part of this literature review. The empirical section examined not only the accuracy and functionality of the Altman Z models but also the characteristic of the model variables by comparing their values in bankruptcy and non-bankruptcy groups.

The data for the thesis was from Bureau van Dijk's Orbis database. Financial data was collected from the database and used for the study. The data included a total number of 80 companies, of which forty were bankrupt and forty were active. A sample of bankruptcy companies was first collected. Then, active companies were selected as a paired sample with bankrupt companies. This was made on a stratified random basis. Bankrupt companies had gone bankrupt in 2018-2019. The latest financial statements were from 2017-2018. Overall, the sample included financial statements from 2013 to 2018. Altman's model classification accuracy was studied one, two, and five years back from the time of bankruptcy.

According to this study, the Altman Z model's operating ability is still decent. Especially, Z'' can classify correctly with good accuracy for up to two years before bankruptcy. However, a longer time period before bankruptcy will reduce the model's ability to predict. In the last year before the bankruptcy, the model correctly classified companies with the accuracy of 78% and two years before bankruptcy the accuracy was still 71%. Regarding this, the results of the study can be considered similar to many other previous studies in the field of bankruptcy prediction.

On the other hand, the results were surprising for the Z' model, which is designed specifically for private manufacturing companies. The model can hardly predict bankruptcy companies even one year before the time of bankruptcy and is unable to add value for decision making if the time period extends. This might be due to the fact that when Altman built the model, the manufacturing companies had a very different company structure. Nowadays, manufacturing companies can have multiple business areas, which might include more or less services. For example, manufacturing companies usually offer repairing and maintaining services as a part of the product. As a result, the Z 'model developed long ago may no longer be reliable. Indeed, Shumway (2001) states that Z-score models are outdated and can no longer be used to predict bankruptcies reliably. Based on the findings of this study, for Z' model, this seems to be the case. The model seems to be outdated and should be only be used with great caution. However, it is good to be cautious about the results of this study as the sample size was rather small and country-specific.

Many stakeholders, such as shareholders, lenders or even executives need tools to assess the financial health and creditworthiness of a company. For example, this may be an analyst who wants to screen a supplier's financial situation before

a large and expensive order. The Altman model provides such tool for stakeholders. It has the advantages of being easy to use, as the Z values are easy to calculate. The model is also free and easily accessible to everyone.
However, the weakness of the model is that it is the so-called late warner, since the financial statements are only a symptom of the crisis, caused by for example a poor profitability of the business. (Laitinen 1990: 157). This is especially true for companies that are not publicly listed because the information required for the Altman model can be obtained only annually from financial statements. The model is also quite old and its coefficients and discrimination zones might require updating.

In the global economy, the business environment is constantly changing. Therefore, the development of bankruptcy research must try to keep up with the fact that as the business environment changes, so do the factors that may cause companies' financial crises. One interesting topic for future research could be whether market data could also be utilized in bankruptcy prediction of unlisted companies. Predicting bankruptcy has been an interesting topic for almost a century, and it is exciting to see where future bankruptcy investigations go.

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ATTACHMENTS

Attachment 1. Sample companies from collected from Orbis database.

Bankrupt Group	Non-Bankrupt Group
AB KUNIMEK OY	RMR OY MERIRAKENNE
ARITERM OY	AIM SERVICES OY
FINN-BRASS OY	ATROTECH OY
FORMADOS OY	CUSTOM PARTS OY
FRAMILLA OY	E V-PINTA OY
FREESTEEL OY	EROMANGA OY
GOODTECH ENVIRONMENT AB	HARMAN TAONTA OY
HAPI-KEITTIOT OY	HTT-GROUP OY
HELSINGIN MEIJERILIIKE OY	HUOLTO MAKI OY
HITSAUS & ASENNUS LUOMASET OY	KALANNIN KALUSTE OY
HJ. JOUSI OY	KARAVA OY
JOPTEK OY COMPOSITES	KONEKORJAAMO A. NUKARINEN OY
KALUSTEPINNOITE KORHONEN OY	KONEVEISTO RAUTIO OY
KALUSTE-PROJEKTIT OY	LAUTAPELIT PISTE FI OY
KANKAANPAA WORKS OY	LIPERIN HOYLAAMO OY
KARELMENT OY	LUMIKKO OY
KASINE TM OY	METALLIVALIMO ARNIE OY
KUOPION KAAVAPALVELU OY	MT-STEEL OY
KYYJARVEN SAHA OY	NANA EUROOPPA OY
LIHATEAM OY, PUNKALAIDUN	NL-NAHKATUOTE OY
MAINIOPAINO OY	NORTHWEST SHIPBUILDING OY
MAINOS-HERKULES OY	OKAY STYLE OY
MASTER PROMO SUOMI OY	OY HANGO MEKANISKA AB
MECANIA AUTOMATION OY	OY SCUTUM AB
METALLIRAKENNE METSARANTA OY	OY TRIAL AB
MS-PINNOITUS OY	PIENKONEHUOLTO LIIMATAINEN OY
NAUTICAT YACHTS OY	PRONIKO OY

OVIKONE GROUP OY OY VALAISIN KEAK BELYSNING AB	R.K. SALON LAKKITEHDAS OY RAHOM OY
PEURA TALOT OY	RAUTARAKENNE S. LIPPONEN OY
PINTAKASITTELYLAITTEIDEN ERI-KOISLIIKE AKATEG OY	AB HANGO SLACKARSERVICE - HANGON SAMMUTINHUOLTO OY
PK KAPPI OY	SATAHAMMAS OY
POLARSOL OY	SWEET CARROTS SC OY
PROXION SOLUTIONS OY	TEKHAM OY
PT-WORKS OY	TEKO-KAIHDIN OY
SENCILION OY	THAI CAFE LOHJA OY
TAAR-GROUP OY	TOIKA OY
TARKKUUSKONEISTUS OY VATAKO	VAAPPUTARVIKE J.HUHTALA OY
TERAHUOLTO J. KIURU OY	YOUNGEST FASHION OY
TOIJALAN TS-PRINT OY	YT-RAUTA JA AANI OY